

# Structural identifiability of parallel pharmacokinetic experiments as constrained systems

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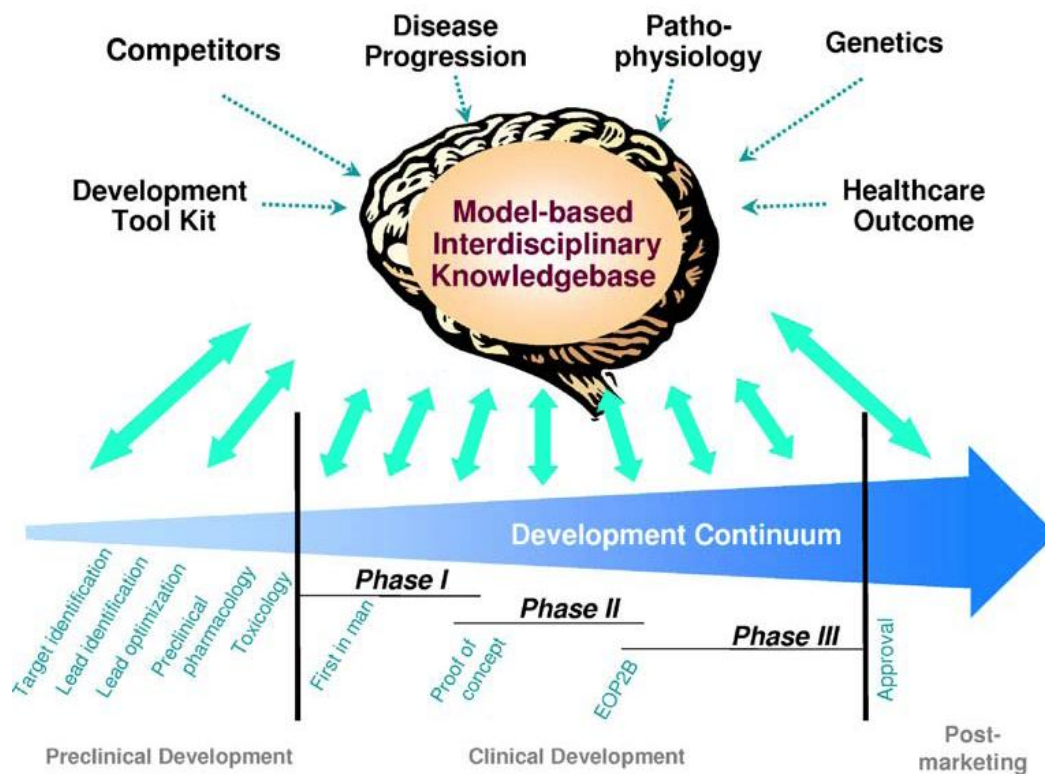
University of Warwick Easter Vacation School 24<sup>th</sup> Mar 2014

# Outline

- Background
- Methodology
- Case studies
- Conclusion

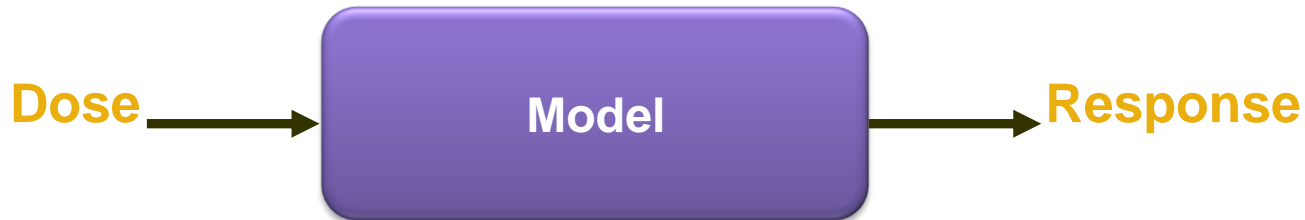
# MBDD — Model based drug discovery and development

- Integrates emerging animal, clinical data and literature to inform decision making process
- Based upon model based inference
- Key to this, is **robust parameter estimation** and awareness of potential alternative model based explanation of data
- **Structural identifiability and parameter identifiability** is an important step in ensuring this



The development continuum adapted from Zhang L. et al. (2008)

# Structural Identifiability



Given postulated state-space model, are the unknown parameters uniquely determined by the output (i.e., perfect, continuous, noise-free data)?

Necessary theoretical prerequisite to:

- Experiment design
- System identification
- Parameter estimation

# Formal Definition

Consider following linear system:

$$\begin{aligned}\dot{x}(t) &= A(p)x(t) + B(p)u(t) \\ x(0) &= x_0(p) \\ y(t) &= C(p)x(t)\end{aligned}$$

$p$  = unknown parameter vector

$p = p_1, \dots, p_q$ ,  $x = x_1, \dots, x_i$  and  $t \geq 0$

A *uniquely globally identifiable model*

→ a unique set of parameter values ( $p$ ) can be determined by the experiment.

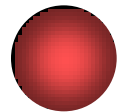
A *locally identifiable model*

→ there exists a finite sets of distinct parameter values ( $p$ ), which produce the same i/p – o/p.

An *unidentifiable model*

→ there exists an infinite sets of parameter values ( $p$ ), which produce the same observed behaviour.

# SIA methods



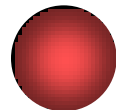
1. Laplace-transform approach



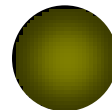
2. Taylor series expansion approach



3. Similarity transformation approach



***Linear Model***



***Non-Linear Model***

# Similarity Transformation Background – linear model

- For any linear compartmental models, it can be written in the form:

$$\dot{x} = Ax + Bu$$

$$y = Cx$$

where **A** is the system matrix; **B** is the input matrix and **C** is the observation matrix.

# Similarity Transformation Method

- **Controllability**

**We can move the model in any direction we like**

- **Observability**

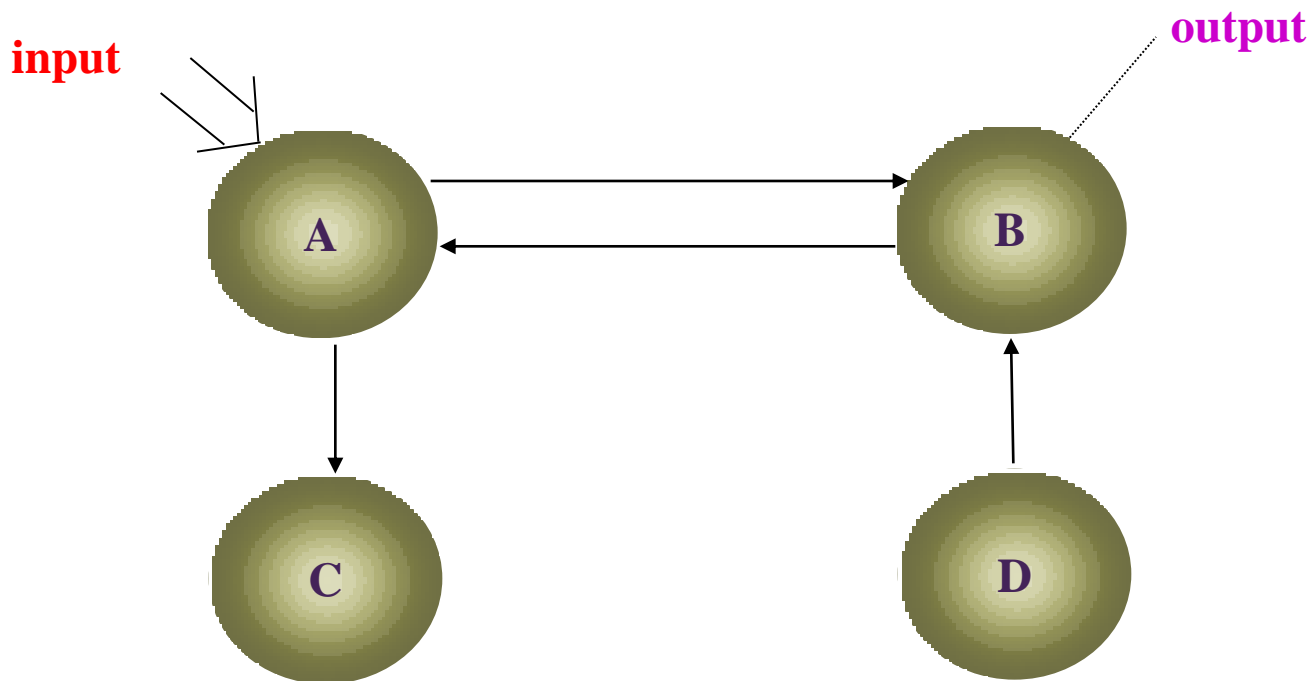
**Our observations tell us what is happening internally**

- **Existence of Transformation on State Space**

**We can move between two models without any apparent change**

# Example

- A,B,C are input connected.
- A,B,D are output connected.
- These are necessary conditions for controllability/observability.
- So D is not controllable and C is not observable (if starting condition is not known).



# “Symptoms of unidentifiability”

- Parameter optimization does not converge.
- Poor %SE when data seems to be reasonable.
- Different estimates dependent upon initial estimate.
- These are all possible indicators of an identifiability issue.

# Ways to fix unidentifiable models?

- Increase the number of inputs (dose routes)
- Increase the number of outputs (observations)
- Simplify the model structure
- Reparameterisation/parameter list reductions
- Fix parameters (based on prior knowledge)
- Fit model simultaneously across data sets where some part of the system is known to change : parallel experiments.

# Motivations:

- Parameter estimates based on 1 set of data collected from a single experiment – thought to be unidentifiable
- Parameters estimated using 2 sets of data from which the experimental conditions give rise to a perturbation in the values of some of the unknown parameters in the structural model

# Targets:

1. Design strategy of experimental design for the types of observation required to get a uniquely identifiable model
2. Design methodology to incorporate this phenomenon to verify the structural identifiability status of the model

# Similarity transformation approach

For two linear systems  $(A, B, C)$  and  $(\tilde{A}, \tilde{B}, \tilde{C})$ . If the following conditions are satisfied then the systems have equivalent input-output behaviour.

1. The two systems are structurally observable.
2. The two systems are structurally controllable.
3. There exists a non-singular matrix  $T$  such that the systems are similar:

$$A = T^{-1}\tilde{A}T, \quad B = T^{-1}\tilde{B}, \quad C = \tilde{C}T$$

# Constrained Structures

For a compartmental model  $(A(p), B(p), C(p))$

The parallel experiments can be expressed by  $(A'(p'), B'(p'), C'(p'))$

where

$$A'(p') = \begin{bmatrix} A(E^1(p')) & 0 & 0 \\ 0 & \dots & 0 \\ 0 & 0 & A(E^n(p')) \end{bmatrix} \quad B'(p') = \begin{bmatrix} B(E^1(p')) & 0 & 0 \\ 0 & \dots & 0 \\ 0 & 0 & B(E^n(p')) \end{bmatrix} \quad C'(p') = \begin{bmatrix} C(E^1(p')) & 0 & 0 \\ 0 & \dots & 0 \\ 0 & 0 & C(E^n(p')) \end{bmatrix}$$

Here  $E^i : P' \rightarrow P$  for  $i = 1 \dots n$  is a map between the constrained parallel experiment parameters and the individual model parameters.

Notice that

$$\text{dimension}(P') < n \cdot \text{dimension}(P)$$

# Examples when parallel PK experiments as constrained structure are applicable

- Different oral formulations
- Presence/absence of competitive CYP inhibitor\*
- Disease: liver/ kidney impaired
- Gastric emptying

# Factor affecting change of PK parameters

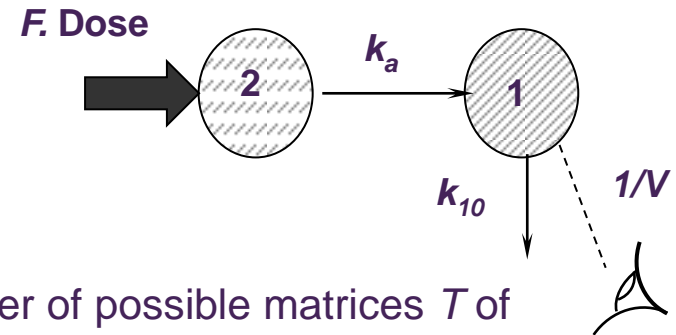
## Different oral formulations

- Oral, (tablet, capsule, solution, emulsion, suspension),
- What affect differentiation to the response if equality of the drug is the same:
  - Excipients (ingredients in addition to additive drug)
  - Manufacturing process
- Different in oral formulation will change the absorption ( $k_a$ ) in the gut and bioavailability (F)

# One-compartmental oral model: single experiment


Model written in Matrix form:

$$A = \begin{bmatrix} -k_{10} & k_a \\ 0 & -k_a \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ F \end{bmatrix} \quad C = \begin{bmatrix} 1 \\ \frac{1}{V} \end{bmatrix} \quad 0$$



For a given  $p = (F, V, k_a, k_{10})$  an infinite number of possible matrices  $T$  of the form

**Transformation matrix**  $T = \frac{F}{\tilde{F}} \begin{bmatrix} \frac{k_a}{k_{10}} & 0 \\ \frac{k_{10} - k_a}{k_{10}} & 1 \end{bmatrix}$

 = observation

**Unidentifiable**

For  $p_{new} = (V / F, k_a, k_{10})$

$$t_{11} = \frac{V}{\tilde{V}}$$

and hence

$$\frac{k_a}{k_{10}} = \frac{t_{11}}{t_{22}} = \frac{V}{F} \frac{\tilde{F}}{\tilde{V}}$$

The model is thus locally identifiable with two solutions:

$$\left( \frac{V}{F}, k_a, k_{10} \right) \quad \text{and} \quad \left( \frac{V k_{10}}{F k_a}, k_{10}, k_a \right)$$

**Locally Identifiable**

# One-compartmental model: || experiments

|| experiment structure can be written in Matrix form:

$$A(p') = \begin{bmatrix} -k_{10} & k_a^1 & 0 & 0 \\ 0 & -k_a^1 & 0 & 0 \\ 0 & 0 & -k_{10} & k_a^2 \\ 0 & 0 & 0 & -k_a^2 \end{bmatrix} \quad B(p') = \begin{bmatrix} 0 & 0 \\ F^1 & 0 \\ 0 & 0 \\ 0 & F^2 \end{bmatrix} \quad C(p') = \begin{bmatrix} \frac{1}{V} & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{V} & 0 \end{bmatrix}$$

where  $p' = (V, k_{10}, k_a^1, k_a^2, F^1, F^2)$  and

$$E^1(V, k_{10}, k_a^1, k_a^2, F^1, F^2) = (F^1, V, k_a^1, k_{10})$$

$$E^2(V, k_{10}, k_a^1, k_a^2, F^1, F^2) = (F^2, V, k_a^2, k_{10})$$

Gives

**Transformation matrix**  $T = \frac{F^1}{\tilde{F}^1} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$

**P' : Unidentifiable**

However the uniquely identifiable parameter combinations are:

$$p'_{new} = \left( \frac{V}{F^1}, \frac{V}{F^2}, k_a^1, k_a^2, k_{10} \right)$$

**Uniquely Identifiable**

# Factor affecting change of PK parameters

## Presence/absence of competitive CYP inhibitor

- Elimination occurs by excretion (bile, breath, kidney and urine) and metabolism (oxidation, reduction, hydrolysis and conjugation) ~ PhI and II reactions.
- Liver is the major organ for metabolism (other such as kidney, lungs, blood and GI wall)
- Many drugs, oxidation, reduction, enzymes responsible cytochrome (CYP) P450 enzymes CYP1, CYP2, CYP3, each further divided into subfamilies
- Rate of metabolism (CL), bioavailability (F) and fraction metabolised (fm) by particular enzymes can change

# Dextromethorphan (DEX)

- An antitussive agent (OTC).
- Non-opiate properties.
- Active metabolite dextrorphan (DOR), (CYP2D6).
- Data collected form a crossover, randomised and double blinded study.
- DEX placebo, quinidine placebo anteceded at 1 hr.
- DEX (30mg), quinidine placebo anteceded at 1 hr.
- DEX (60mg), quinidine placebo anteceded at 1 hr.
- DEX (30mg), quinidine sulphate 50mg anteceded at 1 hr.
- Plasma and Urine (DEX+DOR)

*Moghadamnia, A. et al, J. Clin. Pharmacol. 56:57-67, 2003*

# Parent-Metabolite Model with Oral Dose

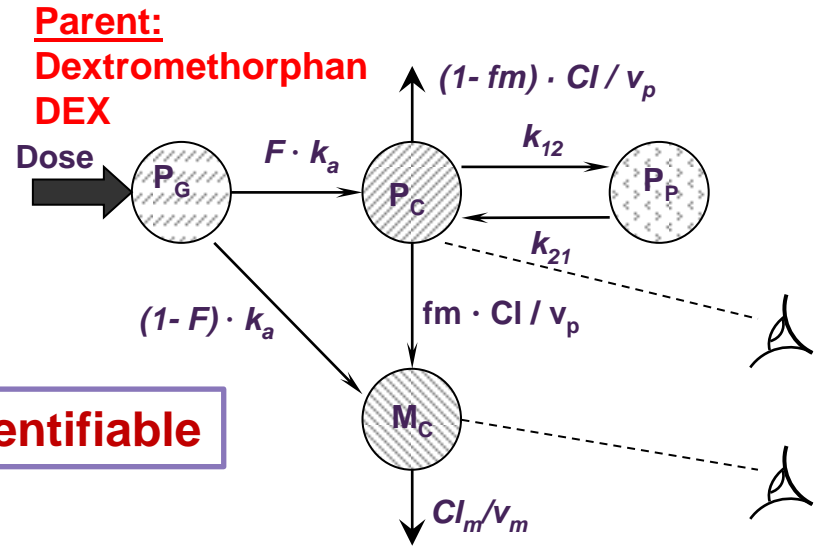
The parameterisation of this model is:

$$p = (V_p, V_m, CL_m, k_{12}, k_{21}, k_a, f_m, CL, F)$$

The identifiable combinations are:

$$p_{new} = \left( \frac{V_p}{F}, \frac{V_m}{1-F}, \frac{CL}{V_p}, \frac{CL_m}{V_m}, \frac{Ff_m}{1-F}, k_{12}, k_{21}, k_a \right)$$

**Unidentifiable**



**Metabolite:**  
Dextrorphan  
DOR

The experiment using the same model structure was:

1. DEX (30mg), quinidine placebo anteceded at 1 hour
2. DEX (30mg), quinidine sulphate 50mg anteceded at 1 hour

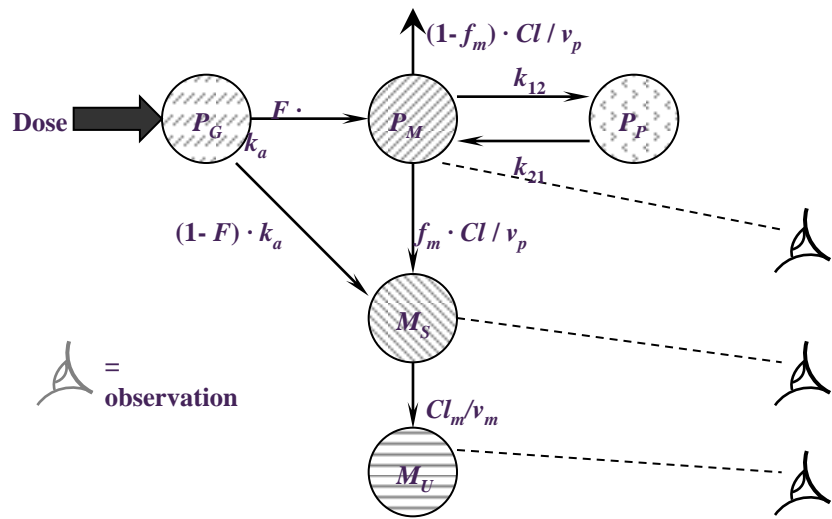
Parameters will remain constant for the two experiments except for those influenced by the rate of metabolism i.e.  $F$ ,  $CL$  and  $f_m$ .

= observation

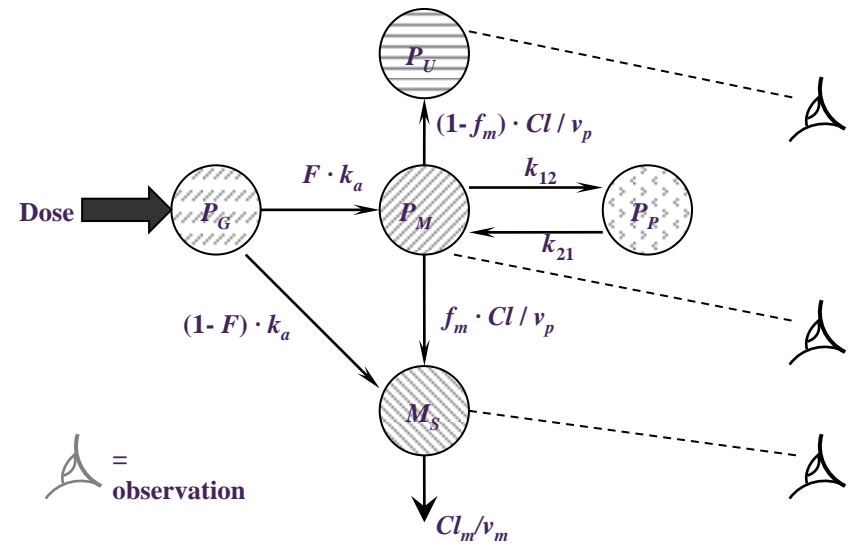
New parameterisation:  $p' = \left( V_p, V_m, CL_m, k_{12}, k_{21}, k_a, f_m^1, f_m^2, CL^1, CL^2, F^1, F^2 \right)$

**Uniquely Identifiable**

# Dextromethorphan (2)



**Uniquely Identifiable**




**Uniquely Identifiable**

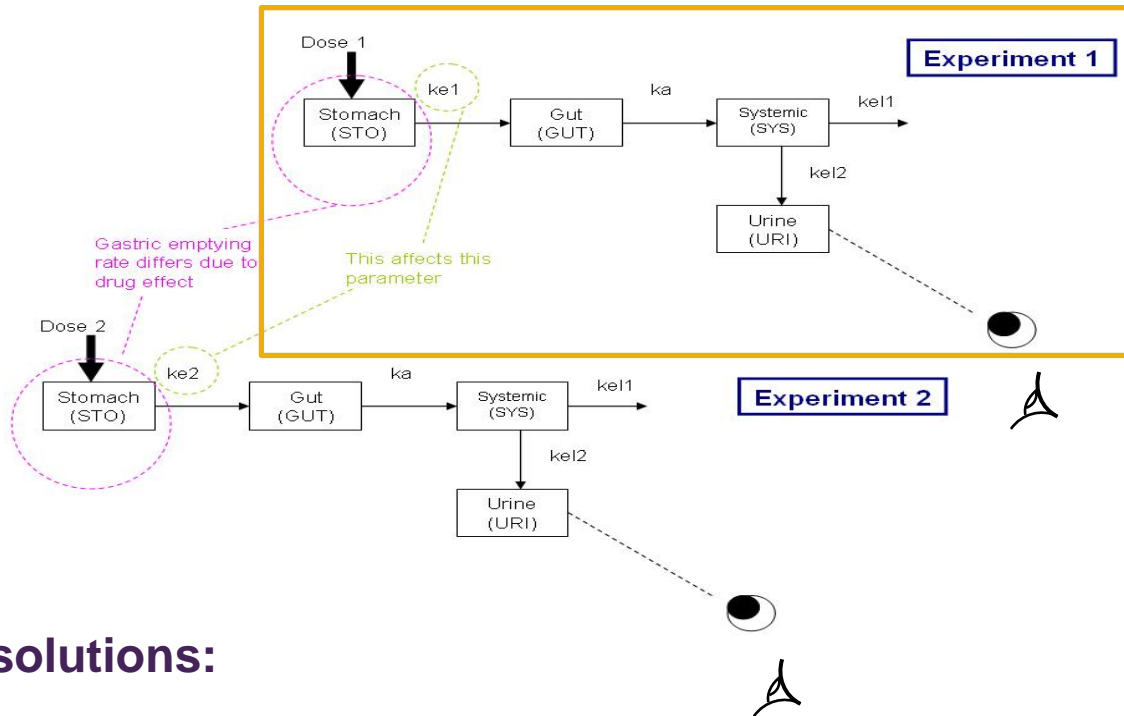
# Factor affecting change of PK parameters

## Gastric emptying (GE)

- Factor determine the absorption kinetics of a drug following oral administration
- GE rates affected by:
  - Food, e.g. fat (slow GE)
  - Drugs e.g. narcotics (drugs that slow contractions in the intestine)
  - Disease e.g. Diabetes (damage of nerve due to high glucose)
- Rate of gastric emptying rate ( $k_e$ ) will change

# GE model

 = observation



**Locally Identifiable**

$k_{e1}$ ,  $k_{e2}$  = gastric emptying rate  
 $k_a$  = absorption rate  
 $k_{el1}$  = non-renal elimination rate  
 $k_{el2}$  = renal elimination rate

3 solutions:

$kk_{el1} \rightarrow k_{el1}$ ,  $kk_{el2} \rightarrow k_{el2}$ ,  $kk_a \rightarrow k_a$ ,  $kk_{e1} \rightarrow k_{e1}$

(The trivial solution - the parameters are the same)

However, we have extra 2 solutions:

or


$kk_{el1} \rightarrow (k_a \cdot k_{el1}) / (k_{el1} + k_{el2})$ ,  $kk_{el2} \rightarrow (k_a \cdot k_{el2}) / (k_{el1} + k_{el2})$ ,  $kk_a \rightarrow k_{e1}$ ,  $kk_{e1} \rightarrow k_a$

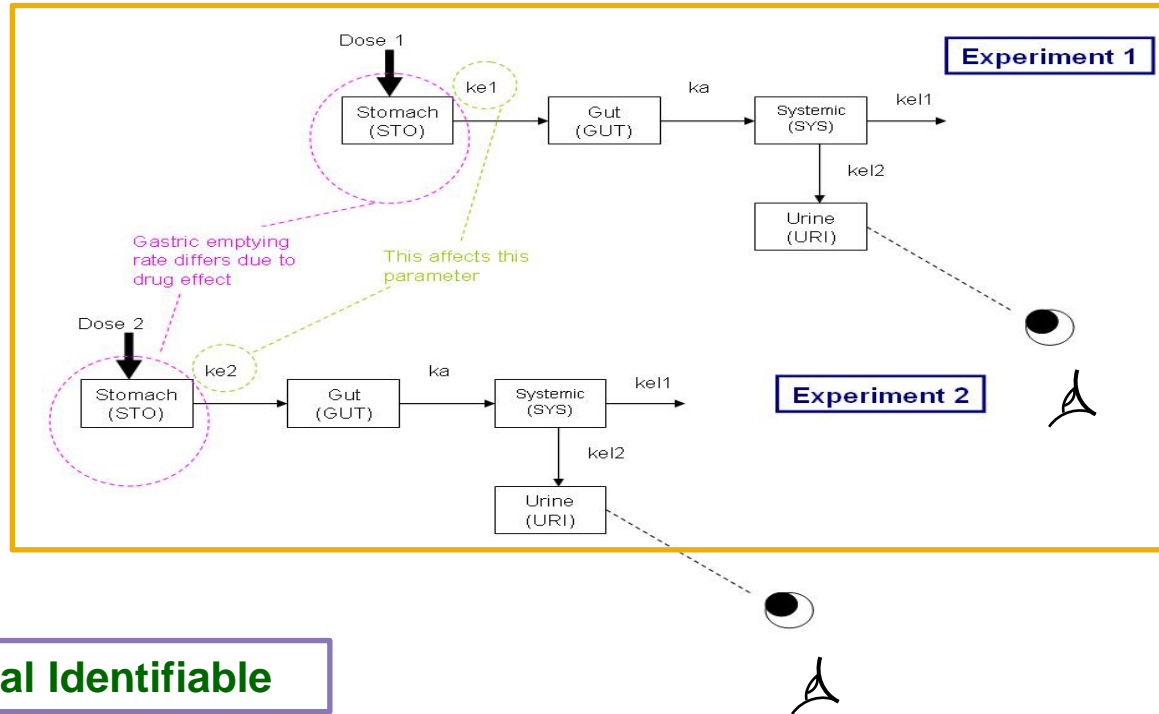
or

$kk_{el1} \rightarrow (k_{el1} \cdot k_{e1}) / (k_{el1} + k_{el2})$ ,  $kk_{el2} \rightarrow (k_{el2} \cdot k_{e1}) / (k_{el1} + k_{el2})$ ,  $kk_a \rightarrow k_a$ ,  $kk_{e1} \rightarrow k_{e1}$

$pbar_i = p_i$

# GE model

 = observation



**Global Identifiable**

- $k_{e1}$ ,  $k_{e2}$  = gastric emptying rate
- $k_a$  = absorption rate
- $k_{el1}$  = non-renal elimination rate
- $k_{el2}$  = renal elimination rate

$pbar_i = p_i$

# Conclusion

- Parallel experiments to enhance the structural identifiability of pharmacokinetic models have been implicitly discussed previously (Nelson and Schaldemose 1953; Moghadamnia *et al* 2003).
- A formal formulation and analysis of this experimental design problem
- A preliminary formulation has been presented here that places the concept of a parallel experiment in the context of a single constrained model structure
- 3 case studies have been examined in order to illustrate the constrained model concept.
- Incorporation of prior knowledge into parallel experiment model structures with constrained parameterisation allows sufficient information to be present in the input-output behaviour to give unique parameter estimates.
- It is apparent from the results presented here that parallel experiment strategies can be very powerful in providing globally structurally identifiable pharmacokinetic models.

# Remarks

- Globally (unique) identifiability  $\neq$  good fits to experimental data
- The techniques do not required physical data for the analysis but instead symbolic algebra obtained from the model description are manipulated to seek for the identifiability status.
- Lack of identifiability does imply that for every parameter estimate, there will be at least one alternative parameter existed that fit the data sets equally well.
- If a model is unidentifiable, infinite sets of parameters will be found and these will cause difficulties in parameter estimation.
- The analysis is carried out with assistance of symbolic computation software MATHEMATICA, MAPLE etc.
- Limitation will depend on computational power available and skills of analysis
- Structural identifiability analysis is a model validation crucial to experimental design, system identification and parameter estimation, therefore important to MBDD.

**Thank you**